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AI-Driven Vehicle-to-Grid (V2G) in Smart Grids: A Theoretical Study

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Abstract. With the development of new energy and renewable energy in recent years, it has become increasingly difficult to meet the rising demand for power from the electricity network. Electric vehicles (EVs) can offer distributed energy storage services for peak and valley regulation and frequency regulation of the power grid via a two-way vehicle-to-grid (V2G) system to improve the flexibility and stability of the power grid. Based on artificial intelligence (AI), this paper presents a unified framework for load forecasting and battery health-aware reinforcement learning scheduling, dynamic pricing, and multi-agent collaborative control to achieve high-efficiency V2G operation in large-scale smart grids. Based on the study of related research, this paper examines the prospects of the framework for improving grid stability, reducing operating expenses, promoting the use of renewable energy and extending the service life of batteries, as well as key problems such as battery degradation, network security, system interoperability and regulatory constraints. Based on the above, it can be seen that the present model is mainly theoretical and simulated, without supporting large-scale empirical data. In the future, based on actual operation data and pilot projects, improve the accuracy of battery aging models and user behaviour differentiation analysis to promote the practical application and optimisation of this framework.

Keywords: Deep Learning, Electric Vehicle (EV), Battery Health Management, Demand Response Optimization

1. Introduction

The accelerating trend toward renewable energy sources includes solar and wind, which significantly increases the variability in power systems and is problematic for matching supply with demand. EVs offer a partial solution too - EVs can serve as distributed energy storage by implementing bidirectional Vehicle-to-Grid (V2G) systems such as peak shaving, frequency regulation, and valley filling instead of using an EV solely for transportation. Integration of EVs replaces Evs transport with grid services for a multi-hour parked state without compromising user convenience. Smart grids serve to implement ICT thoroughly, have automated control improvements, and decentralized coordination of resources - a compatible co-origin to respond to changing electricity levels allowing EPSs to be able to provide appropriate schedule for user needs. ICT typically implements communication standards, such as ISO 15118 to govern secure and trusted data for bidirectional power flow, or ISO 15118-20 to communicate the dynamic price with the user

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when charging [1]. AI replaced the need for solver analysis improvements in quantifying control problems in the energy grid. Using AI in complicated systems such as the energy grid adds complexity, deep learning (DL) and reinforcement learning (RL) improvements in accuracy exhibited anomaly detection, forecasting, and even scheduling in energy systems [2]. More recent studies suggested promising results in employing RL to V2G scheduling successfully, and the simulations produced other optimal outcomes for load variance and cash flow [3, 4]. In summary, few works proposed a coherent structure that integrated forecasting, scheduling, control, and pricing parameters relative to battery health and cybersecurity. This study proposes to fill this gap in V2G engineering literature.

This study proposes a broad theoretical framework to build and operate V2G systems at scale in smart grids using artificial intelligence (AI) techniques including machine learning (ML) and reinforcement learning (RL). The framework covers demand forecasting, scheduling with battery health considerations, energy pricing, and multi-agent control methods. The paper reviews the analysis results of the existing literature to highlight performance improvements, long-term sustainability, technical challenges, and policy considerations.

2. Ai-driven V2G system architecture and modeling

The system concept is to build an intelligent vehicle-to-grid (V2G) system based on artificial intelligence. It is mainly composed of electric vehicle fleets, aggregators, distribution networks and AI intelligent agents, aiming to achieve centralized coordination of charging/discharging scheduling, load forecasting and dynamic pricing. The system adopts a multi-agent control architecture (see Figure 1), modeling electric vehicle users, aggregators and grid operators as intelligent agents in a cyber-physical environment. Electric vehicles have characteristics such as battery capacity, state of charge (SOC) range and departure deadline, and all charging stations are under the management of the aggregator. The aggregator receives real-time electricity prices, load forecasts and frequency signals from the power grid and transmits this information to the AI agent. The AI agent makes optimization decisions based on this, assists in managing the charging and discharging scheduling of vehicles, and introduces restriction mechanisms in the regulation process to extend battery life.

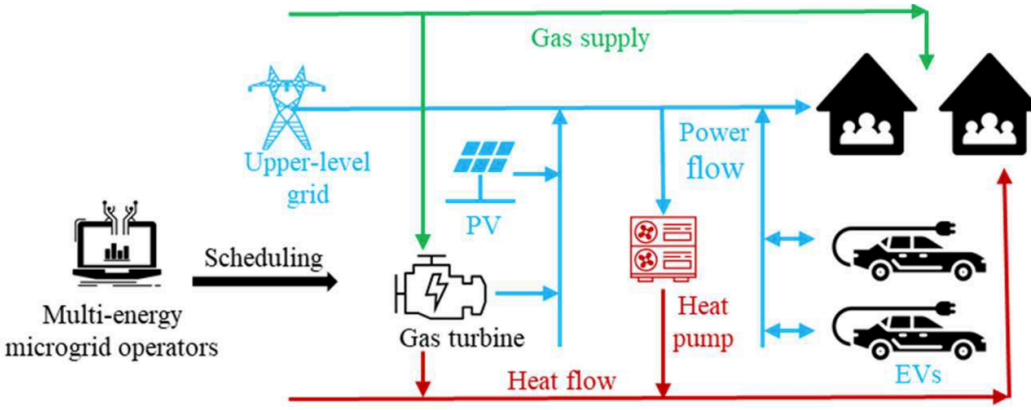

Figure 1. V2G multi-agent control architecture coordinating EVs, aggregators, and grid operators

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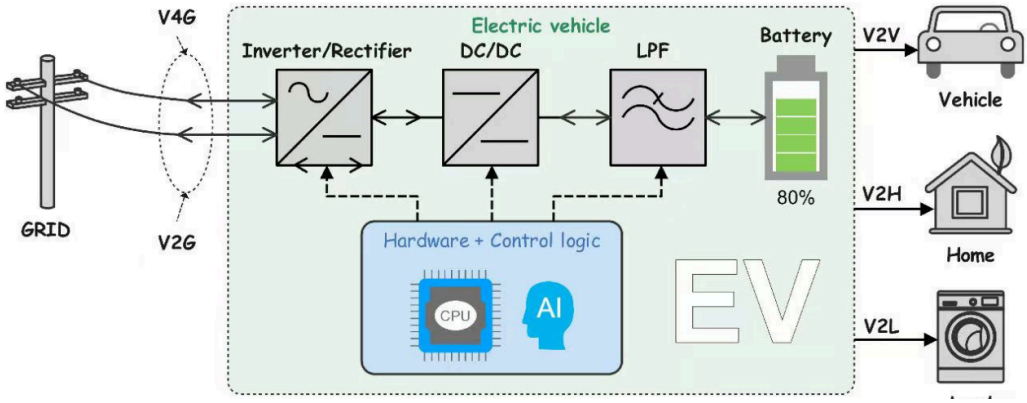

Figure 2. System diagram of AI-driven forecasting and control loops among EV batteries, smart chargers, grid, and edge-AI agents

The AI agents will also be able to communicate dynamically, and securely with one another (Figure 2). Each agent will be specified in the RL formulation, the agent's state (e.g., SOC value, remaining time to depart, anticipated load, price), each agent's possible actions (charging, discharging, or idle), and the reward function for each agent's action. The reward function will represent multiple tasks: savings, load levelling, battery degradation, and keeping the grid stable. The forecasting components will use Deep Learning (DL) algorithms, specifically those using deep neural networks (like Long Short-Term Memory (LSTM) or convolutional neural networks (CNN) to model short-term demand, renewable generated energy, and price movements in order for the agent(s) to make informed decisions. Many papers have shown that DL can represent an improvement in forecasting accuracy against traditional methods [5].

3. AI algorithm integration and scheduling

3.1. Predictive modeling

Accurately forecast the demand for electricity and new and renewable energy resources, as well as changes in electricity prices, to build a smart-energy dispatch system. Accurately predict to reduce operating uncertainty and enhance the efficiency and stability of the system. Martínez-Torres and colleagues have shown that long short-term memory (LSTM) neural networks perform better than traditional feed-forward architectures and have reduced the forecast error rate by 15-25% in cases with long-term dependencies [6]. Based on the above analysis, the framework will use multiple sources of data for collection, such as real-time energy consumption data from smart meters, forecasts of solar and wind power generation provided by weather APIs, and historical charging behaviour data for electric vehicles (EVs). The above multiple sources of data are used to train the reinforcement learning model and build a deep reinforcement learning (DRL) dispatch strategy continuously. Add time series data and external factors, such as changes in the environment (such as weather) and users' behaviour patterns, to improve the prediction accuracy of demand response events and dynamically adjust charging-discharging decisions.

3.2. Reinforcement learning for V2G scheduling

DRL is based on sequential decision-making in conditions of uncertainty. Interestingly, the variance of the load is minimized and the State of Charge (SOC)/State of Health (SOH) can be conserved by

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the DRL methods (Deep Deterministic Policy Gradient (DDPG) and Proximal Policy Optimization (PPO)) and multi-agent RL (MARL) (such as the multi-stakeholder hierarchical implementation of the DRL approach as introduced by Zhang, Chen, and Li in [3]) compare the performance of the standard methods of control. In addition to operational efficiency, their reported metrics showed that their simulations reflected a 97% decrease in load and that 22% of their use of renewable energy increased. New developments of safety-aware DLR also using constrained-based Markov Decision Processes can be used to further address the concerns of battery degradation by including SOH constraints during training and ensuring real-time compliance when making decisions, since it is obvious that battery cells degrade. According to the results of the experiment, the average SOH increase will be only 3% per year, but it will also involve a 10% decrease in Lifecycle Replacement Cost per customer using an electric vehicle (EV). After all, without compliance for safe electric vehicle behaviors and expectations, EV customers will not be willing to accept the increased risk.

3.3. Dynamic pricing with AI agents

We consider the features of real-time pricing as the model includes them within the agent strategy when forecasting total or scheduled buy/sell tariffs based on grid peak load level usage effects. Part of Escoto et al.'s proposal considered the introduction of a dynamic pricing signal to the speed-sensitive relay in comparison to the responses of the physical controller) or aggregator of the EV behavior, in response to predictable grid behaviour, reflected in the price signal transparently. It also highlighted price- based demand shifting methods could support reductions in peak load by an average 10%, simultaneously improving GHG and social- economic performance outcomes of stakeholders [6, 7].

4. Coordination architecture and control strategies

Centralized control, enabled by aggregators, produces globally optimal decisions while scalability and privacy restrictions apply. Alternatively, federated multi-agent structures afford better resilience and privacy but require more sophisticated coordination protocols. Indicatively, in the application environment of the electric vehicle (EV) infrastructure of Thailand, the multi-agent reinforcement learning (MARL) protocol proved to have some significant benefits over the traditional benchmark strategies, not only in that the use of the multi-agent reinforcement learning (MARL) protocol will result in an increase in the occupancy rate of the charging stations of about 12 per cent., but also in that the use of the multi-agent reinforcement learning (MARL) protocol will result in the reduction of the average waiting time of the users by a significant number. Moreover, the edge computing nodes in the smart grid have the responsibility of processing local real-time data streams such as key parameters like frequency, voltage and temperature to ensure that the system is capable of having a response time of milliseconds or even lower to enhance the dynamic adjustment ability and stability of the system. Regarding the issue of the security of communication between electric vehicles and the charging infrastructure, the application of the international standard of ISO 15118-PKI framework and the design of an AI-based intrusion detection system has become the key to ensuring that the communication between electric vehicles and the charging infrastructure is secured. To effectively differentiate between normal and abnormal behaviors, Sharma et al. [8] proposed an anomaly detection model with high detection rate of a network security incident to demonstrate the promising potential of AI technology in network security protection. Not only does resilience manifest itself in the effectiveness of the system control, but also underlines the need to be prepared to respond to different emergencies at any given time to ensure the proper and continuous

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functioning of the system [9]. It has significant importance in assuring the stability and security of smart grids and electric vehicle charging systems.

5. Discussion

Based on various theoretical simulations and case studies, the effectiveness and feasibility of AI-driven V2G systems have been demonstrated to some extent; thus, they are likely to be added to future smart grids. The synthesis of results in the literature offers supporting data for the above operational and environmental benefits. For instance, by applying reinforcement learning (RL) and deep learning techniques in a system, about 76% of the daily cost of EV charging has been reduced through optimal scheduling and dynamic price forecasting [9]. Load variance at the grid level dropped by as much as 97 per cent, improved power quality and frequency stability, and reduced the stress on transformers and substations. A particular use case for the ability to forecast and flatten demand curves is in power grids with high proportions of intermittent renewable energy generation, such as wind and solar. In addition, the reduction in emissions achieved by various studies in the literature ranged from 18% to 22%, and among these, those related to EV charging and discharging were closely aligned with periods of excess renewable energy generation [4]. Through intelligent scheduling strategies that incorporate the constraint of the State of Health (SOH), the impact on battery health in terms of SOH was an improvement of 10%-15% in SOH life expectancy; thus, it can extend the economic service life of EV batteries and delay replacement costs in the long run. The above performance indicators will serve as empirical support for demonstrating that, under the conditions of appropriate hardware and communication standards, and in cooperation with all parties, an AI-powered V2G platform can be practically implemented to deliver actual benefits.

Despite these promising outcomes, several critical challenges and limitations remain. First, battery degradation continues to be a primary concern. The V2G operational process includes frequent charging and discharging cycles leading to capacity fade which may discourage EV owners from being participants. For now, AI models must develop a reward function that incorporates SOH-aware constraints that prolong battery health while fulfilling their commitment to the grid [4]. Second, due to the level of connections associated, there is an increased cybersecurity risk within V2G systems. The many interactions between EVs, aggregators, and the grid, with in-the-moment connectivity for thousands of units, increases opportunities for attacks on all parties. While AI-based anomaly detection algorithms have been quite effective so far - e.g., garnered 98% + detection ability [8] - these will not eliminate the risk of zero-day attacks or adversarial attacks. This means specification-based encryption, intrusion detection systems (IDS), and the ability to propagate security patches will remain critical. This said, the scope of V2G will require a coordinated policy and regulatory effort to mitigate the challenges of V2G and fully leverage the opportunities of AI-enhanced V2G systems. Moreover, through e.g., tax incentives, grants for V2G-compatible infrastructure development and smart chargers and bidirectional inverters, governments can play a uniquely impactful role. Compliance with communication protocols such as ISO 15118 would also contribute to improved interoperability throughout the ecosystem. Likewise, developing a licensing regime in which aggregators were legally recognized as intermediaries between EV owners and grid operators would engender a new role that both enhanced oversight/responsibility, and reflected the smart and modernized relationship between these entities. Tariff designs that are dynamic are continuously adapted based on modelling from AI forecasting exercises, meaning more predictable and equitable pricing mechanisms can be developed without sacrificing grid reliability.

Pilot programs in places like the United Kingdom and California have demonstrated the feasibility of V2G integration at scale and the lessons learned can support more significant

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deployments. These pilot initiatives should ramped up through public-private partnerships to stimulate commercial readiness. On the global stage, authorities such as the Institute of Electrical and Electronics Engineers (IEEE) and the International Electrotechnical Commission (IEC) would need to come together to harmonize jurisdictional standards, notably in cybersecurity certification, transparency in AI algorithms, and data protection across standards. Only by coming together will communities and the coordinated effort of AI-based V2G systems move from the promise of their theoretical potential, to future intelligent sustainable energy systems.

6. Conclusion

In conclusion, this paper creates a unified AI-enabled framework for V2G integration in smart grids. It integrates predictive modelling, battery-aware RL scheduling, dynamic pricing, and multi-agent coordination across an edge-enabled architecture to provide measurable improvements to grid stability, costs, renewable penetration and battery health. Within image schematics, EVs were shown to have coordinated layered relationships with aggregators and distribution grid. While the benefits are clear, there are still significant challenges still, including battery degradation, cybersecurity, interoperability, as well as regulatory complexity. This study also has some deficiencies. Given that the research is theoretical and simulation-based, it has not been verified through large-scale empirical experiments on actual V2G operating data. The application scope and performance of the new system under different network environments and user usage patterns have not been comprehensively verified yet. In the future, it will be necessary to introduce large-scale real-world datasets and pilot project results for validation and optimisation of the AI algorithm and system design in this study. Improve the accuracy of scheduling and user satisfaction through an all-encompassing model of battery aging and user heterogeneity.

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